Discrete Event Simulations for Scalability Analysis of Robotic In-Field Logistics in Agriculture – A Case Study

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***Abstract*— Agriculture lends itself to automation due to its labour-intensive processes and the strain posed on workers in the domain. This paper presents a discrete event simulation (DES) framework allowing to rapidly assess different processes and layouts for in-field logistics operations employing a fleet of autonomous transportation robots supporting soft-fruit pickers. The proposed framework can help to answer pressing questions regarding the economic viability and scalability of such fleet operations, which we illustrate and discuss in the context of a specific case study considering strawberry picking operations. In particular, this paper looks into the effect of a robotic fleet in scenarios with different transportation requirements, as well as on the effect of allocation algorithms, all without requiring resource demanding field trials. The presented framework demonstrates a great potential for future development and optimisation of the efficient robotic fleet operations in agriculture.**

I. INTRODUCTION

The introduction of robots into agricultural domain is expected to yield impressive productivity gains as well as improving produce quality and traceability. As the agricultural domain is generally very labour intensive, introducing automation in relatively small doses, rather than aiming to automatise entire operations, can have significant positive impacts, both in terms of productivity as well as in workers' health and well-being [1].

In this paper we present a powerful simulation framework to analyse the economic viability and potential of automatising logistics tasks in soft-fruit production operations using a fleet of autonomous mobile robots. We present the utility of employing a *Discrete Event Simulation* framework, coupled with robots' path planning ability, in order to run and evaluate many different scenarios in short periods of time. When it comes to actual deployment of robotic fleets in agricultural domains, the question that needs answering is about

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(a) An aerial view of the investigated strawberry farm. (b) Robot Thorvald adopted for in-field logistics.

Fig. 1: Our case study: robotic in-field logistics in agriculture.

the optimal size of the fleet and the modification of operations that go along with their introduction, as well as an assessment of the scalability of the respective approaches. We make a contribution towards answering these questions with a generic simulation framework, evaluated and discussed in a specific scenario and discuss the lessons learned from this initial assessment.

The core contributions of this paper are:

1) A novel *discrete-event simulation* (DES) framework, modelling the interaction between logistic robotic fleets and human soft fruit pickers in the field (Sec. III),
2) A *case study* of the proposed DES framework, based on quantitative data gathered in a pilot study (Sec. IV), and
3) The assessment and discussion of *scalability and economic viability* in in-field logistics (Sec. V).

II. RELATED WORK

Agricultural robotics is an emerging technology being deployed at different stages of food production including applications such as precision seeding [2], weeding [3] and harvesting [4]. Agricultural and food logistics has important role in ensuring food quality and on overall health of the personnel involved [5]. Fleets of autonomous transportation robots have been predominantly used in warehouse applications [6] with many recent attempts in precision agriculture [7], [8].

Many of the existing work in in-field agricultural robotics focus on the multi-robot path planning [9], [10], and very few have looked at collaborative interactions between humans and robots. The costs associated with introducing a robotic fleet should be justifiable in terms of improved productivity and quality or reduction in other costs. As environments can vary, and different types of robots are available at different costs with different functionalities, this optimisation problem may be solved by simulating the processes and observing the effect of having fleets of different sizes and types. A direct approach would involve simulating continuous-time models of the processes. This, however, could result in long simulation runtimes when the state of the process does not change for a considerable amount of time. An alternative approach is to discretise the processes and running a DES looking at the changes between the important states that are of interest.

III. DISCRETE EVENT SIMULATION

In a DES model of a system, the basic unit which changes its state is known as an *entity* which compete among themselves for capacity limited resources. The entities in the DES described here are human workers and robots in a farm. A *resource* is an element providing some service, and is usually capacity-limited. Here, robots are examples of resources providing transportation service and are available in finite numbers. A step change performed by or on an entity is known as an *operation*. In case of a robot assistant, going to the assigned worker location for providing assistance is an operation. An *event* is a set of operations happening at a time instance resulting in n a change of the system state (consisting of the states of individual entities). A DES jumps through different event times and updates the states of entities and the whole system. A detailed overview of the DES concept is available in [11].

The DES discussed here is developed using SimPy [12], a discrete event simulation framework in Python as a Robot Operating System (ROS) [13] package enabling easy integration with a wide range of existing mapping and robot navigation algorithms in ROS. For example, the DES makes use of an existing ROS package [14] for path planning and navigation.

IV. THE RASBERRY PROJECT

A. Project Aims

The RASberry project (Robotics and Autonomous Systems for Berry Production) aims to develop autonomous fleets of robots for horticultural industry. In particular, the project considers strawberry production both in a traditional open ground fashion and in polytunnels. The first major objective is to support in-field transportation operations to aid and complement human fruit pickers, followed by other objectives on applications such as plant treatment, yield forecasting and fruit picking. To achieve this goal, the project will bridge several current technological gaps including the development of a mobile platform suitable for the strawberry fields, software components for fleet management, in-field navigation and mapping, long-term operation, and safe human-robot collaboration.

$20-30\,\%$ of the labour time is spent walking crates of picked fruit and empties back and forth from the crop to the ends of field/greenhouse and on farm logistics hubs. In addition, around $10\,\%$ of the field area is designated for transportation needs (access for tractors, lorries, etc.). The proposed fleet for in-field transportation will eliminate the need for workers to carry picked crop and replenish them with empty crates. In addition, the transportation infrastructure can be significantly reduced since the robots do not require special arrangements. The robot will be equipped with a dedicated picking crate storage and weight sensors for basic quality assurance. This functionality will enable more precise traceability of the produce and more precise yield estimation. The in-field transportation is a universal problem for production of various crop and hence the results of the project will be directly transferable to other domains.

B. Modelling the RASberry use case

The scenario considered in this use case consists of a close representation of a real strawberry production site located in the Southern Norway. The site features an open rectangular field containing 28 parallel rows of strawberry plants, each $120\,\mathrm{m}$ long and separated by $1.5\,\mathrm{m}$, resulting in $3360\,\mathrm{m}$ of total row length covering an area of $0.5\,\mathrm{ha}$. The resulting topology of the site corresponds to a *comb* pattern with the main transportation route containing the local store connecting starting points of all rows (see Fig. 2).

In a traditional setup, a group of human pickers assigns themselves into individual rows and carry on picking until their crate is full. The full crate needs to be transported to the local store located in front of the rows and aligned roughly with the middle row. When a picker reaches the end of the row, the picking process continues on the other side of the strawberry plant row until the picker returns to the beginning of the row. If

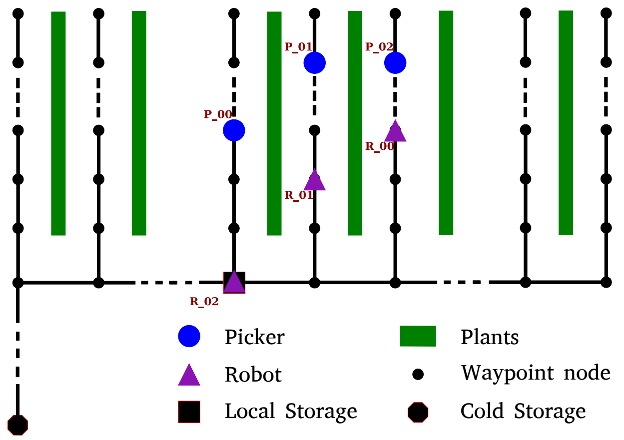


Fig. 2: A representative visualisation of the RASberry-DES with three pickers and a fleet of three robots.

there are still unallocated rows, the picker selects the first free one and carries on with the picking process. A common deviation from this sequence of operations is during warm weather conditions, when the full crates are unloaded at a cold storage facility rather than the local storage to ensure product quality. As this cold storage may be at a distance from the farm (hundreds of metres or more), the pickers will have to travel farther whenever the crates are full.

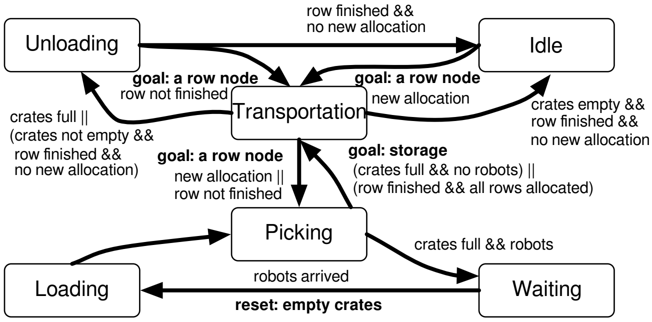
The robot-assisted picking consists of a fleet of N robots which are assigned to individual human pickers as soon as they complete a single tray using one of the considered task allocations algorithm. The robot travels to the assigned picker who then loads the full tray onto and collects an empty one from the robot so that they can carry on picking immediately after the robot has left their location. The robot with the full tray travels to the local/cold store, unloads the cargo and then becomes available for all future tasks.

We have conducted a short real field experiment to measure the main characteristics of the manual picking process undertaken by a group of 14 human pickers working during 4 hour period. The picking of the entire block took approx. 4:08 h (14880 s) resulting in 87 completed crates in total. The observed picking rate followed a normal distribution of 2408 ± 90 s (mean $\pm$ std) and estimated loading time was 110 ± 44 s per crate. The rough transportation speed is assumed the same for all pickers at 1 m/s.

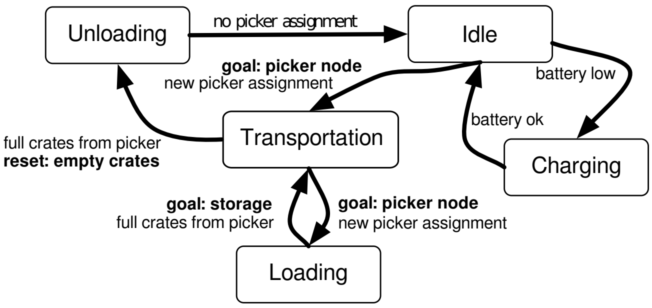
In the DES of RASberry usecase, all the required parameters of the farm area and picker models are calculated from the above observations. Each farm row is discretised into a set of nodes placed along the row. This distance is set as 5 m for the experiments reported here. The yield from each row is also assumed to be normally distributed with 0.0650 ± 0.0013 crates per node distance. The same field is used for all simulations with a total yield of 86.68 crates. There is assumed to be only one local storage at the head of the 14$^{\text{th}}$ row and a cold storage at a distance of 250 m from head of the starting row. In order to differentiate the performance of different pickers, the picking and transportation rates are assumed to be normally distributed, 0.0375 ± 0.0007 m/s and 1.00 ± 0.02 m/s respectively (received from field observations). When there are robot agents, the pickers are assumed to take the same time to load the full crates on the robot, as they would have taken to unload at the local/cold storage. All robots are assumed to have the same transportation rates and unloading time. It is also assumed that the pickers will transport and unload any partially filled crates to the local storage station, when they finished picking the last row allocated to them, and there are no more rows to be allocated. A schematic visualisation of the agents (see Fig. 2), with updates at each event time, is also provided. The picking process is discretised by looking at the changes in picker states while moving from one topological map node to another.

The picker agents have six different states, namely idle, transporting (moving to a row node to start picking or to a storage station for unloading), picking, unloading, waiting for a robot to arrive, and loading on a robot. A picker will reach the last two states only when there are robots. The robot agents have five states, namely idle, transporting (to a picker or to the storage), waiting for picker to load, unloading at local storage and charging. The transitions between these agent states are shown in Fig. 3a and Fig. 3b.

The picking process is initially simulated with pickers alone, and then with different number of robots for transporting the crates. It is assumed that only one picker is allocated to a row. When robots are available, a robot is assigned to only one picker at a time. i.e., the robot is available for further assignments only after unloading the crates from picker in the current assignment. It is also assumed that there is no capacity limitation at the storage stations. A picker, once completed the current row will be allocated to the next unallocated row. Robots are assigned to pickers using *lexicographical* and *uniform utilisation* methods. Lexographical ordering (of their identification tag) is used to resolve any deadlocks. This greedy allocation is similar to the one observed in real farms. In the *uniform utilisation* method, the scheduler will try to



(a) State diagram of a human picker.



(b) State diagram of a robot assistant.

Fig. 3: State transition diagrams, shown with conditions that trigger them, and state variables being set.

distribute the tasks across the fleet, such that they all are uniformly utilised. Ten trials of each experiment is performed to observe the variations. It will be possible to extent the DES with other task allocation algorithms.

V. ANALYSIS

A. Validity of the manual picking simulation.

In order to check the validity of the manual picking simulation, the DES was initially run without any robot agents. The average process completion times observed were $15094.77 \pm 124\,\mathrm{s}$, compared with the observed $14880\,\mathrm{s}$ in the field study. This increase in the process completion time, $1.44\,\%$ of the actual data, was expected as a result of the randomly distributed picking and transportation rates. From the actual field study, it was observed that each picker has to travel (with speed of $1\,\mathrm{m/s}$) approximately $124.64\,\mathrm{m/crate}$ to unload at the local storage station approximately. On average a picker is allocated to two rows, resulting in an additional $21\,\mathrm{m}$ travel to the start of a row, after the picker is allocated to a row (total transportation time of $145.64\,\mathrm{s}$). From the simulations, each picker spent approximately $140.33 \pm 14.80\,\mathrm{s/crate}$ in transportation state for approximately 6.19 crates. This change in the transportation required ($3.65\,\%$ decrease from the actual) are also in the accepted range. Moreover, the simulations were fast enough to run multiple trials. Even the slowest of the simulations reported in this paper took less that $7\,\mathrm{s}$ to simulate all the events in $4{:}08\,\mathrm{h}$ clock time on a workstation with Intel® Core™i7-3770 CPU and 16GB RAM.

B. Picking performance with a robotic fleet under low transportation requirements

These experiments were performed to inspect whether introducing a robotic fleet would improve any performance metric, and what would be its ideal size, under low transportation requirements. In these experiments, the scheduler would assign an idle robot to a picker, as soon as he requested for one. The robots would carry empty crates to the picker and brings full crates to local storage. The time a picker would wait for a robot is same as the time to travel to the local storage. As the picker can resume picking after loading the robot, there by saving the time a human would have taken to return from the local storage. In an actual farm, unloading crates at local storage was found to have a low transportation to picking time ratio ($6.75\,\%$). As the robotic fleet was mainly reducing pickers' transportation, the margin of performance improvements in these experiments was very small.

Variation in the total completion time, and corresponding picker utilisation for the simulations with the number of robots varied from zero to 14 are shown in Fig. 4. Picker utilisation is represented as a percentage of the overall process completion time. It can be seen that the completion time was very high for small number of robots and started decreasing as there were more robots, with the crossover taking place for seven robots. Correspondingly the picker utilisation also went above that without the fleet. With seven robots, there was $0.84\,\%$ decrease in the completion time and $1.21\,\%$ increase in the picker utilisation. With 14 robots, these values were improved to $3.59\,\%$ and $3.13\,\%$ respectively. The high completion time for small number of robots was a result of the long duration for which pickers had to wait to get access to the limited resource (robot assistant). As the number of available robots was increased, the waiting time was reduced.

The performance gains with robot fleet seem marginal from these experiments, mainly due to the low transportation to picking time ratio ($6.73\,\%$). A robot fleet would have more influence in cases where the picking time has a lower ratio to other state times. Examples for such scenarios include polytunnels, where the plants are on raised beds resulting in faster picking

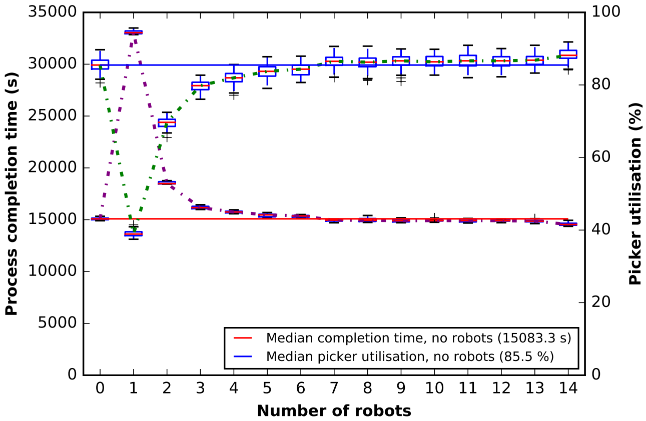


Fig. 4: Box plot of task completion time and picker utilisation with different fleet size and transporting to local storage

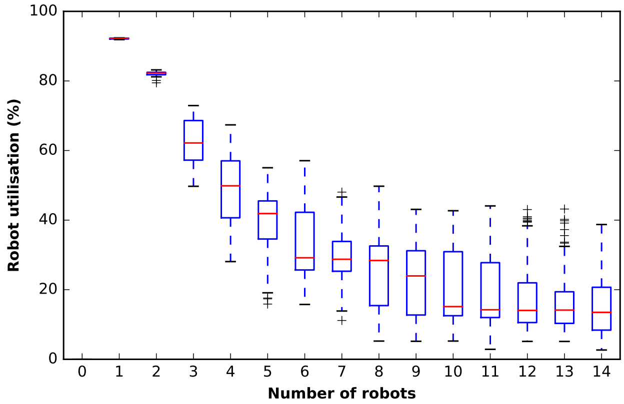
and when full crates need to be transported directly to a cold storage. We consider such a case in Sec. V-D.

C. *Utilisation of the fleet under different task allocation strategies*

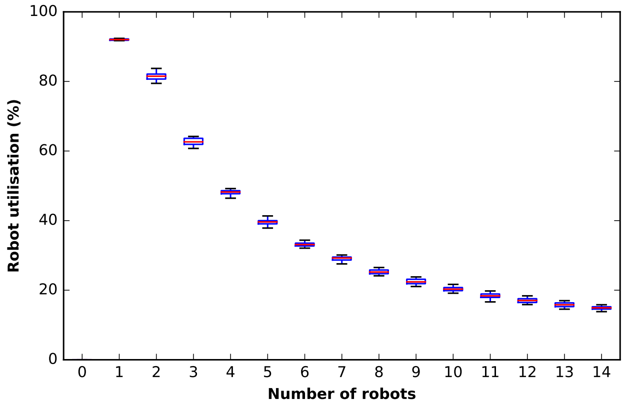
In the simulations discussed in Sec. V-B, robots were assigned using *lexicographical* allocation. Further simulations were carried out with *uniform utilisation* approach, to investigate the influence of allocation algorithm on the performance of the fleet. Theimprovements in the total completion time and picker utilisation from those with *lexicographical* allocation were minimal, but noticeable variation in the individual robot utilisation (robot's working time as a percentage of the total completion time) was observed. The box plots of robot utilisations are shown in Fig. 5a and Fig. 5b for *lexicographical* and *uniform utilisation* allocations respectively. Although the average utilisation is similar for both the methods, there was lot more variations in individual robot utilisation with *lexicographical* method. This is because the *uniform utilisation* method considers the time robots worked so far, before making a new assignment. From these experiments, it was concluded that algorithms used for robot allocations influenced individual robot utilisation and between the two approaches tested, *uniform utilisation* was the better one in making sure no robot is over-used.

D. *Picking performance with a robotic fleet under high transportation requirement*

Another set of experiments was performed to look at the performance variations without and with a fleet under higher transportation requirements. In this, full crates were transported directly to a cold storage 250 m from the farm (see Fig. 1 and Fig. 2) resulting in a high transportation to picking time ratio (30.93 %). Allocations were performed using *uniform utilisation* approach. A box plot of the task completion time and corresponding picker utilisation (picking time as a percentage of the completion time) observed in these simulations are shown in Fig. 6. In comparison to the earlier set of experiments (see Sec. V-B), it took longer to complete the process due to the increased transportation. With the pickers alone, it took approximately 3410 s (22.61 %) more than the earlier set of experiments. With a fleet of five robots, the processing time came below that without a fleet, resulting in a decrease of 2.48 % in completion time and an increase of 1.65 % in the picker utilisation. With a fleet of 14 robots, the completion time was decreased by 19.75 % and the picker utilisation was increased by 16.79 %. With small fleet, pickers' waiting times to get a robot were higher resulting in high completion times.



(a) Using *lexicographical* allocation.



(b) Using *uniform utilisation* allocation.

Fig. 5: Robot utilisation as percentage of process completion time while using different allocation strategies.

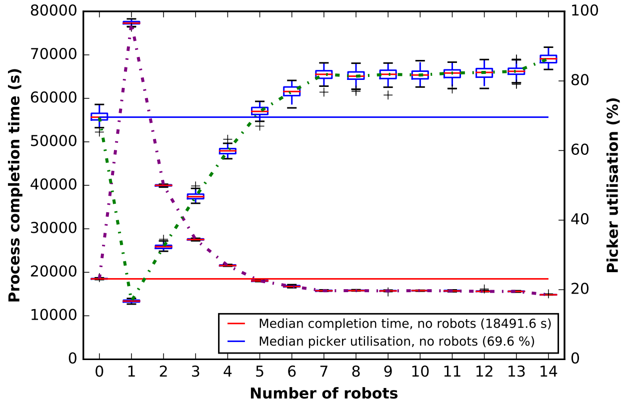


Fig. 6: Box plot of task completion time and picker utilisation with different fleet size and full crates unloaded at the cold storage

VI. CONCLUSION AND OUTLOOK

The utilisation of a discrete event simulation allows the rapid analysis and exploration of different scenarios and processes in the in-field logistics domain, including state-full interaction between a robotic fleet and human workers. It has been shown that the overall timing of the simulation results is as little as 1.44% deviation in overall task completion time when compared to the actual field study, indicating viability of the simulation model to study different work flows without requiring resource expensive field trials. Another positive aspect of introducing a robotic fleet is on the pickers' health, as they no longer have to transport the full and heavy crates. The optimal number of robots for the actual farm considered here with 14 pickers, as a trade-off between improving overall completion time, pickers' waiting time and costs of robots, is approximately 5-7.

From the actual case study, two key lessons can be learned:

1) In this prototype, human pickers actively requested a robot only if and when they had finished picking. Hence, they had to wait for the robot to arrive which consequently undermines productivity gains. *Anticipatory scheduling*, where the scheduler can estimate when a robot is needed a picker's location, will address this issue and is at the centre of our future work within the RASberry project.
2) While without robots, a local collection station is needed in the vicinity of the picker rows, we have shown that a change of operations where the robots take the freshly picked fruit straight to the cool storage can be implemented with only little more investment into robots, unleashing potentials to improve the product quality.

We believe, it is these changes in operational patterns and routines that will unveil the true potential of in-field logistics, and DES is a viable way to analyse the scalability and economic aspects of different process implementations. Possible future work includes application of different existing allocation algorithms for robot allocation and considering anticipatory arrival of picker requests to reduce picker's waiting time.

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